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Survey on models and methodology for emergency relief and staff scheduling

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Abstract

Decision support is required for effective planning on all kinds of scheduling scenarios. The stochastic scenarios and uncertainty in demands make the scheduling task complex. Multiple objectives in terms of cost, timing window, priorities and travel routes are the driving factors in the scheduling task. These objectives are often associated with given constraints like time, cost, resource limit etc. To meet all these objectives with the given constraints, it requires effective scheduling methods. Among different application areas of scheduling, emergency relief and staff scheduling are two domains which present major challenges for the scheduling research. These two areas provide analogy with many other areas of scheduling. Issues like finding appropriate locations and establishing them in appropriate group, discovering effective path for routing and making efficient plan for distribution and servicing are major challenges for these two and related scheduling cases. This paper covers a survey study on some of the recent papers of these areas that highlights the problem formulations, technologies, methods and algorithms applied. It provides a literature review on technologies and algorithms applied in the area of emergency case relief scheduling and staff scheduling.

Keywords: Resource scheduling, Staff scheduling, Emergency relief

1. Introduction

Scheduling systems are used to manage and optimize access to service providers. Several factors occur that affect the performance of scheduling systems including availability of resources, services, time variability, service preferences, information availability, level of the scheduling. For each scheduling environment relevant plans, ranging from a set of rules to the real-time responses are described that guide schedulers. There are many private and public organizations which provide relief distribution or staff services to the people. Each of those may have different scenarios, objectives, interests, capacity, and expertise but have common objective of scheduling optimization [36]. Scheduling service starts with requirements. In most of the cases, the requirements are in forms of estimation, mostly done by experts. The schedulers are typically equipped with resources having specific time windows [37]. Schedulers must handle volume flexibility, delivery flexibility, and supply system flexibility for effective and efficient management [1].Schedulers have to work in such way that they can handle critical and challenging issues like minimizing unsatisfied demands in case for goods or services allocations to seekers [7, 8]. Major objectives and constraints during the scheduling are to minimize cost, unsatisfied demand, travel time, and rational resource distribution. Satisfying these objectives are the major challenges in scheduling task. To meet the objectives, there are some constraints that make the job complex. Some of the very commonly faced constraints are stochastic supply and demand, resource availability, and vehicles routes.

Conventionally, planners are likely to create schedule for services and resources manually conducing to the issue related to travel distance, travel costs and resource utilization. All services and resources cannot be accomplished within their specified time windows according to insufficient manual schedule [38] since there are multiple objectives. Traditionally, solving such a problem consists of converting multi objectives into a single objective function [19]. The desired goal is to find the best solution that minimizes or maximizes this single objective while retaining the constraints of the problem. Compared to a single objective problems multi-objective problems are more difficult to solve, because there is no unique solution; rather, there is a set of acceptable trade-off optimal solutions. The solution algorithms of such problems should be shifted from exact to heuristic or meta-heuristic due to the complexity of the problem. To solve these multi-objective problems, heuristic methods are generally used. Some of commonly applied approaches are as: Nearest Neighbour Heuristic, Genetic Algorithm, Memetic Algorithms, and

Particle Swarm optimization. These were developed with different algorithms and techniques but they have the same target to minimize the total cost and maximize preferences for both resource and staff scheduling.

There are numerous areas where scheduling is required for effective planning, decision making and task implementation. Among several applications of scheduling optimization, we choose two areas to review in this paper: emergency relief scheduling and staff scheduling. These two scheduling problems characterise the many features of the general scheduling and present challenges for the researcher. Several techniques, approaches, models and algorithms have been applied for scheduling solutions that make the best use of the corresponding objectives and constraints. In case of emergency such as in disaster relief operation, efficient scheduling plan reduces the severity of the impact of the emergency. The optimized scheduling of relief item distribution not only helps decision makers to plan effectively, but also to implement timely. For the case of staff scheduling, it requires improved schedule plan so that there is minimization of cost, time and maximization in the service satisfaction level. It needs optimized scheduling to balance between the skill level and time window. Scheduling task has number of issues. Appropriate resource centre location, transportation path and proper allocation and distribution planning are among the issues discussed in most of the cases. Each issue has impact on the efficiency of the scheduling decision making.

This paper surveys the recent papers on these two areas. The survey focused on the key issues of scheduling task in terms of pre-positioning, transport and routing and resource scheduling. We focus on the solution techniques and algorithms that are used to improve and optimize scheduling task. The rest of the paper is organized as follows. In Section 2, problems associated with scheduling task are discussed. In Section 3, different techniques, models and algorithms are considered. Analysis and discussion is accomplished in Section 4. Conclusion and future research issues are discussed in Section 5.

2. Problem classification and models

There are many sources of uncertainty in scheduling that may affect coordination efforts. The nature, the location, timing, intensity of sudden needs, population characteristics and pre-existing regional infrastructure such as communications, transportations are the major concerns in the scheduling. The scheduling may also be challenged by the counter-active problem such as oversupply, unwanted and unused resources for longer period. Among many issues of scheduling, we review some of the key issues in scheduling managements and are categorised into following sub groups.

2.1 Pre-positioning, warehousing and clustering

One of the major goals of emergency relief scheduling effort is to provide services or resources as effectively and as timely as possible. In order to achieve this goal, several types of supplies, scheduling plans and decision making are essential during the distribution period. Pre-positioning of service centres at strategic locations is obligatory so that the commodities are available when they are needed [**10, 11**]. Where to preposition supplies in preparation for a scheduling is one of the key issues. Developing an effective pre-positioning of resource centres are challenging because of the uncertainty occurrence of demand locations and their magnitudes. The location and capacities of the service providers are key components in managing response efforts after an event. There can be a single resource distribution centre or number of such centres. A resource network is a collection of multiple resource centres, characterized by connecting link and storing capacity, built to address specific services or resource demands. The network needs to be designed to optimize timely distribution of the items. All the resource centres need to be modifiable to meet the optimum demand-supply when distribution starts. Based on the presented assessment parameters and constraints, resource network optimization methods could be developed. A resource network may exhibit different behaviours in different stages of scheduling.

Designing the network with appropriate location and storing capacity is challenging since network structure dynamically evolves [**9**]. There can be different alternatives to supply centre locations. If supplies are located closer; it can allow for faster delivery of supplies [**12**] but the major threat is that the supplies may be in a risky location for the cases such as if any the disaster occurs. If supply centre is located far, it increases the transport cost and delay in distribution. Considering these risks, determining the optimal location, stocking quantity and the total expected costs associated with delivering to a demand point from a supply point is required. Supply points at different locations may have different probabilities of being shattered and may offer different travel costs/time to serve the demand so in the network of resources centres cooperation and collaboration is required for optimum result.

2.2 Transportation and Connecting Network

Scheduling models that are able to accurately interact and represent the reality may be more desirable. In some scenarios, information about accurate need is hard to obtain, and a stochastic modelling approach can be useful to represent those scenarios. Transportation and connecting networks design depends upon location and also the specific challenges of resource distribution. Transportation and routing problems are very difficult to solve. The problem's difficulty increases as the model's level of detail increases [**4**]. Trying to solve all issues at once, stochastic data, heterogeneous vehicle fleet, in a multi-period and multi-commodity network context, the resulting model will be complex to solve. The resulting model may not be optimum solution when looking for fast and efficient solutions. Therefore choosing the factors that are best suited to the context and then establishing hypotheses on the other features is required to simplify the model.

In most of the scenarios, transportation capacities often exceed the available capacity significantly and vehicles depart from and arrive to warehouses with full load. Therefore, it is not quite possible to modify the vehicles route whenever new information arrives. One of the issues during the transportation is the last mile distribution problem [**5**] that arises in case of emergency response which involves delivery from local distribution centres or from central warehouses to a population in need. It included both delivery and pickup functions, and call it ''the last mile delivery and pickup problem'', where the last mile delivery is concerned with materials transported from warehouses to affected locations. For the logistics distribution, not only finding the best path is enough for vehicle routing but it is also important to find the capacity of the path along with the vehicle [**6**].

The vehicle routing problem can be further sub-categorized as path finding and network flow capacity. Both the sub problems have its own constraints that need to be considered while finding optimum method for logistic support routing. An essential issue is capacity feasibility because of the vehicle capacity fluctuate throughout the route path and also the assignment of the multiple types of load to available vehicles with different capacity and type. These parameters keep changing dynamically during the disaster relief system. Another challenge in the path selection is condition of the path that also keeps changing with respect to time in scenarios such as emergency cases [**8**]. Path condition is a time varying function that depends on the parameters of the path description. Objective of cost minimization varies with the path conditions with varying time. For transportation, one task is to design the transport network and another is to optimize the route selection for a specific task [**15**].In planning and scheduling problems route scheduling is required to find effective routes for offering service to the demand points with the shortest path.

2.3 Resource Distribution/Scheduling

Distribution of commodities and services in the disaster struck areas with quick response is a critical issue for emergency relief. Resource distribution is challenging because of it stochastic nature of occurrence and inadequate information. A critical and challenging component of distribution is the allocation of resources to the beneficiaries [**2, 3**]. The major objectives and constraints during the resource distribution or scheduling are broadly classified as:

i. Minimize cost: Minimize the running cost of resource distribution task. This mainly includes travel cost and inventory costs and other operational costs. Operational cost of emergency distribution is different than the business operational cost because the decisions taken during the emergency are more diverse.
ii. Minimize unsatisfied demand: Demand in most of cases is stochastic and varies rapidly with time. For affective distribution operation within demand areas, minimization of unsatisfied demand is required.
iii. Minimize travel time: Timely arrival of commodities is required. To achieve this, the shortest path or the minimum time for travel is desired.

Above listed objectives are the major challenges in distribution job but it also has some constraints that make the job complex. Some of very commonly faced constraints are:

i. Stochastic supply: The quantity of goods available at different supply centres with the network for distribution is varying and in most cases that may not meet the exact demand in distribution phase.
ii. Stochastic demand: The amount and type of commodities and services request vary with time and also that vary from one location to another location.
iii. Vehicle Availability: Types of vehicles availability, capacity, cost, travel time varies. Also there can be single or multiple dispatch point in the distribution network.
iv. Vehicles routes: Finding the shortest feasible route from distribution node to end node is another constraints for distribution implementation.

Timely distribution with minimization of cost is required during distribution process [**19, 20**]. Apart from these two objectives, another objective during the distribution of minimization on unfair distribution to all points [**20**]. Minimization in unfair distribution is as higher as possible is essential but cannot reach to the level of 100% is challenging since the demand within the network is stochastic in nature.

Workforce resource is also one of the most difficult issues associated with constraints in case of service scheduling, even when they have only a single criterion and homogeneous skills [**54**]. This problem also concerns about when and how the workers should be employed with their skills. Human resources consist of different task skills[**55**]. They can be categorised into either hierarchical task or categorical task skills. Under hierarchical task skills, each staff has different efficiency and quality of work where staff with a lower skill level can do less task than staff with a higher skill level. Under categorical task skills there is no difference on performance level. Each staff group has different skills that they can perform in the group. Another challenge for resource distribution is kinds of service to be scheduled. The scheduling model should incorporate the time slot or assignment of each individual worker task. Some service requires only single type resources where as some requires multiple types.

3. Methodologies

In general, real world scheduling problems are multi-objective. For instance, some cases require minimum cost, some require high priority service first, some requires minimum time duration where as some may requires minimum utility utilization such as human resource and vehicles. Most of scheduling scenarios are multi-objective optimizations related to a set of results or solutions called Pareto-optimal solution. In the wider sense, no other solutions in the search space are better when all objectives are considered [**56**]. During the last decade, a number of multi-objective algorithms have been proposed including classical and intelligent approaches. The Classical approach comprises of converting the multi- objective problem into a single problem which can be solved using traditional scalar-valued techniques comprising weighted aggregation, goal programming, ε-Constraint, and discussion on classical method. The second approach is directly a tool to investigate the Pareto-front using Artificial Intelligent (AI)/computing algorithms. The results will be generated in many iteration of the AI search to create and then is analysed in different effective methods. However, the problem of this approach is how to choose to the Pareto-optimal set and how to keep up the convergence of the result.

There are many popular tools which can determine the Pareto capable solution. Vector Evaluated Genetic Algorithm (VEGA) separates the population into several equalled sub-groups according to the number of objective functions to find each objective. Multi Objective Genetic Algorithm (MOGA) is a simple and proficient technique based on Pareto-Based Approaches and Niching Mechanism in [**57**] to create the possibility of answer called "non-dominated individual" which was developed to the Non-dominated Sorting Genetic Algorithm (NSGA). Moreover, Niched Pareto Genetic algorithm (NPGA) and (SPEA) were proposed to handle with multi-objective problems. The former is an algorithm which desires to categorize classification layers in [**58**]. The latter uses an external archive to maintain the non-dominated solutions found during the evolution. Candidate solutions are compared to the archive [**59**].In the next sub-section, a number of methods and algorithms applied for different issues are analysed.

3.1 Pre-positioning, warehousing and clustering

The first stage challenge in scheduling task is to identification of appropriate location of the distribution centre. Also, the appropriate capacities in terms of their storage and availability resources need to be identified. There can be a single or number of distributed locations for resource distribution. Evolution of the resource network can be considered using a discrete-time model to deal with the uncertainty and dynamism. Hu et al. [**9**] proposed complex resource network based on a multi-agent system (MAS). They developed a framework for resource network with the state diagram describing the various states of each resource distribution centre of the network at discrete time interval. Each resource centre was a unit of storage, where the resources were stored in units or blocks depending on their types and properties. Their network was designed for small scale scheduling case for fire disaster that may be applicable for larger scale. Although in the large scale demand, there are many number of distribution centres in the network so network optimization is required. The model also considers gradual decrease in resources availability at distribution centres. But, in most of the long run distribution centres, there occurs in and out of resources from the centre so value of a centre changes over time but not necessarily decrease every time.

Stochastic programming, a general purpose technique, deals with uncertainty in the input values to optimization models and was used for pre-positioning of resource centre. Rawls et al. [**10**] had applied a two-stage stochastic mixed integer program (SMIP) that provides response pre-positioning strategy for emergency threats. The SMIP considered uncertainty in demand for the stocked supplies as well as uncertainty regarding transportation network availability after an event. A heuristic algorithm, Lagrangian L-shaped method (LLSM), was developed to solve large-scale instances of the problem to reduce the computational complexity. The model combined facility locations and sizes of storage facilities. It also considered the amounts of various materials stocked in each facility, decisions on stocking levels for emergency supplies, and distribution of those supplies to multiple demand locations after an event with uncertainty about demand. The model used a set of discrete scenarios with probabilities to represent potential locations and magnitudes of the uncertain events. A bundled commodity was defined that includes specific elements in fixed proportion but was still handled by the algorithm as a single commodity. It did not change the structure of the formulation but changed the decisions to acquire, stock and transport units, commodity costs, storage requirements and other related parameters that reflect the aggregation. Finding appropriate location for storing commodities with sensitivity analysis was applied to show how different parameters impact stocking levels and costs.

Campbell et al. [**11**] showed how cost model can be used to select the single best supply point location from a discrete set of choices. Apart from this it also included how it can be embedded within existing location algorithms to choose multiple supply points taking the constraints on standard inventory purchasing, restocking costs, salvage values and delivery costs. Identifying the supply centres, the algorithm had considered the cost of assigning each demand point to each of the supply points and allocating each supply centre to the demand point where it could be served at the lowest cost. Model could be used to select the single best supply point location from a discrete set of choices but the algorithm failed to identify more than one distinct supply points in case if the demand is not fulfilled by singe supply centre. Barzinpour and Esmaeili [**12**] developed multi-objective mixed-integer linear programming model for preparation of disaster logistics scheduling based on demand area population and damage severity. They applied goal programming approach to prioritize objectives in order to have the least deviation from goals. For the planning, worst-case scenario was considered for need estimation and preparation. The model showed improvement in quality of solutions when collaborative and cooperative between sub-regions were used.

Heuristic algorithm was designed to solve emergency resource allocation problem based on an integer mathematical programming and network optimization. Zhang et al. [**13**]modifies the solutions of the linear programming with constraints of multiple resources by setting priorities of preference for each demand location with certain possibilities. The algorithm was designed to efficiently satisfy the constraints and objective function for scheduling resource distribution by setting allocation priorities according to their probabilities of occurrence. The local search technique was employed to assign the emergency resources to those points based on the set priorities. Mete et al. [**14]** proposed a two stages stochastic programming model to select the storage locations of medical supplies. During first stage, warehouse selection and inventory decisions was done with the objective of cost minimization. During second stage, transportation plans and demand satisfaction decisions were decided which represents the amount of medical supply to be delivered from warehouse to hospital with the minimization on the total transportation duration. The model was limited only to land transportation and used a set of predetermined routes that may not be fully applicable in all scenarios since the condition of the route changes dynamically and uncertain in most of the scheduling cases.

Aghamohammadi et al. [**31**] applied heuristic method based on two nested genetic algorithm for optimal allocation of the distribution centre in the form of medical centre for resource scheduling in case of emergency. It used Geographic Information System (GIS) for positioning data. Among the two nested genetic algorithm, one is applied for location part on the basis of number of population need to be serviced by the medical service centre and the next one is applied for resource scheduling optimization by reducing the operation time.

3.2 Transportation and Network Flow

Sending out resources from distribution centre to demand point cannot be effective without considering the connecting path, available vehicles and their capacity, especially if there is more than one demand points need to be in consideration for scheduling plan. Ozdamaret al. [**5**] used hierarchical cluster and route procedure (HOGCR) for coordinating vehicle routing in large-scale post-disaster distribution and evacuation activities. The HOGCR utilized an efficient network flow model in a hierarchical ‘‘cluster first, route second’’ approach that produced feasible solutions. It offered flexibility in adjusting the solution quality by imposing different runtime restrictions. HOGCR approach divided the demand centres in the relief network into geographically dense clusters using the k-means clustering algorithm and then solved the top-level routing problem. When a cluster had more demand centres than desired its routing problem was not solved immediately, but it was sub-divided further into smaller sub-clusters. Finding efficient and stable cluster in its hierarchy cluster centre requires number of iteration with correct parameters. In the case of emergency, there is very high chance of incorrectness that makes the approach not very effective for early stage of distribution. The initial procedure of the route Scheduling begins by partitioning entire area into sub-areas using clustering.

Generally, clustering algorithm can be divided into two major branches: Hierarchy and Partition [**62**]. The partition clustering illustrates outstanding results compared with the Hierarchy technique. Typically, partition clustering technique has a simple and easy concept to implement by attempts to find to centre of clusters or sections call “centroid” by minimizing an objective function. Simple K-means or modification of k-means was applied such as K-mean such as Kd-tree, K-mean++, Fuzzy c-means [**63, 64, 65**] were applied for clustering. After that, the nearest-neighbour heuristic is used for all clusters by finding the unrouted customer locations “nearest” in terms of a measure of Euclidean distance between its centroid and location. At every repeating loop, the heuristic search gathers the unrouted customer locations into the nearest cluster depended upon its centroids until each cluster reaches the maximum number of members. Thus, using the K-mean in the initial phase is very effective for solving scheduling problem. Although, the K-mean, an iterative technique, is used widely; it has several disadvantages such as difficult to know the number of actual clusters, an iterative technique, a higher chance to fit in bad local optima [**66**].

Yi et al. [**6**] applied a meta-heuristic of ant colony optimization (ACO) for solving the logistics problem arising in relief distribution scheduling activities by decomposing the original logistics problem into two phases of decision making. The first phase builds stochastic vehicle paths under the guidance of pheromone trails while a network flow based solver was developed in the second phase for the assignment between different types of vehicle flows and commodities. With the increase of dimensionality and covering space this approaches might not be the highly efficient techniques. A modified Dijkstra algorithm was designed by Yuan et.al [**7**] to solve the time-varied shortest path problem for routing. A mathematical model was built for path selection in the real-time effect of disaster for emergency logistics management with the objective to minimize total travel time along the path from distribution point to the relief distribution centre. A path selection model for emergency logistics management was built based on path complexity consideration having objectives to minimize total travel time along the path and to minimize the complexity of the path. The complexity of the path was modelled as the total number of arcs included in a selected path. An ant colony optimization algorithm was applied to solve the multi-objective optimization model. The algorithm converts the multi-objective path selection model into a single-objective model. The model considered travel speed under disaster conditions that is different from normal conditions travel speed. The assumption of the model that speeds on each arc of the network will decrease with the extension of disasters in time and space is not valid for all cases. The conditions of the arc need to be updated with varying time and hence the speeds and travel times can be calculated.

For solving problem of emergency transportation scheduling in the relief supply chains, a multi-objective fuzzy optimization was applied by Zheng et al. [**8**] with the consideration of three transportation modes: air, rail, and road. They applied a cooperative optimization method that divides the integrated problem into a set of subcomponents and evolved the sub-solutions concurrently. These sub-solutions were brought together to construct complete solutions. The arrival time at the relief centre was defined by fuzzy number to cope with the uncertainty of travel time of vehicles because of variation of environment. Among the three means of transportation, the highest priority items assigned to air transportation then after to railways and then to road transportation. For the solution, the integrated problems were divided into a set of sub-components and applied multi objective tabu search. After then multi objective genetic algorithm was applied to optimize sub solutions for transportation task allocation and resource allocation. The major focuses were on the optimization of the task allocation plan, resource allocation plan and delivery scheduling and vehicle routing plans where the items priorities varied with time and areas.

Ahn and Ramakrishna [**23**] applied genetic algorithm for routing. The model used variable-length chromosomes with population-sizing equation based on the gambler's ruin model with the major objective to minimize the cost associated with the path. For similar scenarios, Nagata et.al [**24**] used a penalty-based edge assembly memetic algorithm for vehicle routing with time window. The model calculated time window violation and hence the sum of the penalties in the route for vehicle routing. Vidal et al. [**25**] also applied time window for vehicle routing. They used hybrid genetic algorithm with adaptive diversity management to minimize time and cost during scheduling. Zidi et.al [**28**] applied multi-agent approach for vehicle scheduling. The model used guided genetic algorithm that has multiple agents in the forms of system agent, information manager agent, forecast agent, distribution agents and others. It first dealt with the emergency planning with set of request then it concerned with the contingency planning. The contingency plan addressed the issues of new requests or any breakdowns in the scheduled task implementation. It applied local searching for contingency management. The major focus of the schedule was to maximize the number of saved people in case of emergency while also minimizing the cost of the rescue operations. To minimize the transportation service delay during scheduling task, Özdamar and Yi [**34**] applied constructive heuristic model to find the feasible acceptable solutions. The feasible efficient routes were examined based on greedy neighbourhood search based on the vehicle's utilities.

Zhi-Hua Hu [**15**] proposed a multi-objective integer linear programming model to build the path selection for container supply chain in the context of emergency relief. A scheduling framework was proposed for the container multimodal transport emergency relief that was modelled by immune concepts for optimization. Affinity measures were designed to represent the complex relations among the components. Based on the affinity model, a decision process of emergency relief was proposed considering the characteristics of container. The main objective of optimizing the multimodal transport was to choose optimal combination of transport means by minimizing the cost and satisfying the time constraints. It used binary value 0/1 for transportation link that is either the fully conditioned link or no link condition. For transportation scheduling, the connecting link conditions are one of the constraints that need to be considered while finding the effective shortest cost path in the transportation network.

3.3 Relief Resource Distribution/Scheduling

In general, scheduling of resources in most of the cases is close to the supply chain management. The primary objective and actions are similar but the major change or challenge is uncertainty and nature of the information.

On mathematical programming methods, Felici and Gentile [**45**] established an integer programming model that maximizes the total satisfaction of the scheduling of staff with use of positive weights for shifts. Moreover, Bard and Purnomo [**60**]proposed mathematical programming model for minimizing the penalty in scheduling of staff members violating the preferences. They adopted the column generation scheme to solve the problem in which many conflicting factors guided the decision process. M'Hallah, R.

and A. Alkhabbaz [**49**] used a mixed-integer programming model for the staff scheduling problem applied in a health-care unit. They adopted a case study as Kuwaiti Health Care Unit for nurse scheduling for this model. The result showed the better schedule than the nurse manually planned scheduling. Smet et al. [**50**] solved the scheduling problem using a generic mathematical model, which is related to the common elements used in earlier similar works and some limitations that are usually ignored in the medical centres. Fan et al., [**44**] used a binary integer programming model to plan a practical solution of management in nursing timetable. The purposes are to maximize all nurses' satisfaction after considering seven shifts of both 8.5 and 12.5 hours a day and some hard and soft restriction. The model also covered preferences of each staff for creating schedule of selection.

Given the fundamental differences between supply chains scheduling and emergency resources scheduling, supply chain coordination mechanisms might not be feasible or practical for relief scheduling [**1**]. Different methods had been applied for solving these issues. Researchers have applied mathematical approaches and computational methods such as fuzzy logic, genetic algorithm for solving such problem during different phases of scheduling. Camacho-Vallejo et at. [**19**] applied a bi-level mathematical programming model applied where problem was modelled with two different levels of pre-set hierarchy for decision making to get optimum result. The model assumed decision-makers in the upper level called the leader and in the lower level called the follower with set of variables, constraints and corresponding objective functions at each level. The leader made decision based on the actions and the follower reacts accordingly. Doing so, the follower optimized its objective with considering the decision made by the leader. The Upper level chose the means of transportation and the speed of distribution of goods that minimized the total response time for delivering resources and the lower level chose the storage centre with minimized shipping cost. Bi-level model then reduced into a nonlinear single-level mathematical model and hence problem was linearized as a mixed integer programming problem. The model used Chile earthquake (2010) as a case study where it found solutions with lower cost and time for distribution of emergency logistics.

Tzengetet al. [**20**] designed a relief-distribution model with the multi-objective programming method for relief delivery systems. It focused on the objective to minimize cost, time and unfair distribution during the planning period. For the maximization in fair distribution, scheduling model considered even distribution to the demand points regardless of cost by defining the upper boundary limit of the resource demands among all of the relief demand points in each period of distribution. The model assumed need of the people and current connected road network was only considered for the distribution. Wright, P. D. and S. Mahar [**52**] considered staff's preferences to deal with a centralizing scheduling problem with nurses from multiple units such as surgical, medical, and intermediate cardiac units in a hospital using an integer programming process. The method involves in two examining objectives: minimize cost of scheduling and maximize preference with satisfying the constraints of the staff's availability and preferences.

Solution approach used in business supply chain help to identify the major issues that can be used during the other scheduling management. Solution, such as an agent-based micro-simulation framework proposed by Roorda et al. [**16**] represented the diversity of roles and functions of actors in the resource scheduling system. Diverse actors involved in the production and distribution of goods illustrates the major issues of consideration for affective distribution system. Two-stage approach was used to solve the response problem. At first stage, based on primary information, stochastic estimation of transportation capacities, supply availabilities and demand were identified. During second stage, actual values were used as they were revealed. Due to uncertainties associated with the information and a lack of supporting resources pre- and post- operation coordination activities were compared to enhance the effectiveness of the scheduling outcome. Two-stage, decisions of multisource relief supply and relief distribution, demand chain based dynamic optimization model was formulated in the specified emergency logistics co-distribution framework.

Sheu [**21, 22**] in his works proposed a time-varying relief demand associated with each affected area. The demand was predicted using a short term dynamic relief demand forecast model that mainly relied on the number of survivals trapped in the affected areas without receiving any rescue aids and may change over time upon updating the conditions. The model focused on group-based relief distribution having a composite weighted multi-objective optimization to deal with the problem of distribution. It clustered multi-type reliefs from multiple urgent relief distribution centres to multiple affected-area groups that maximized the time-varying relief demand fill rate and minimized the time-varying distribution costs.

Genetic Algorithm (GA) is also one of the effective approaches that were applied for solving scheduling problems. Genetic algorithm has been proven effective for solving optimization problems in various fields. However, GAs essentially uses generation succession to search for optimal solutions. Chou et al. [**18**] applied a Biological-based Genetic Algorithm (BGA) for improving the solution performance and execution time with their optimal solution search capability. It used the highest and the lowest fitness values to normalize chromosome population fitness values between 0and 1. Non-linear fitness values were adjusted by increasing their fitness values with superior chromosomes and eliminated inferior genetic groups by decreasing their fitness values. Higher prioritized areas retained superior chromosomes for use in further crossover and mutation operations. The method increased chromosome population diversity and moved beyond local optimal solutions by using multi point search and imitating the biological phenomenon of migration instead of using mutation. Guided search direction was applied where fitness values were generated from a fitness function instead of from differential gradient data. The computational cost of the BGA was 50% lower than those of the other corresponding algorithms. This approach had a limited use of previous search in the selection, crossover, and mutation operations.

Lin et al. [**26**] proposed a heuristic genetic algorithm approach for scheduling that was designed for logistics model for delivering prioritized items. The model was designed with multi-objective that considered multiple items, vehicles, time periods. It applied weights on the objectives. By applying the weights, the multi objective problem was converted into a single objective problem that minimized the total unsatisfied demands, total travel time for all vehicles and tours. Chunguang et al. [**27**] developed distribution scheduling where genetic algorithm was applied for optimizing the travel route and also determining the number of vehicles being used for relief item. The models targets to total number of vehicles being used and also to minimize the distribution time. The major limitation of the model was that only one kind of resource was considered for scheduling. With the objectives of minimization of unsatisfied demand, delay in service and transportation coat, Chang et al. [**35**] proposed greedy search based multi objective genetic algorithm for resources scheduling. The model dynamically adjusted distribution scheduled from various distribution points as per the requirements from various points. The algorithm adjusted the distribution of available resources by generating various feasible schedules. In addition, it also assembled multiple routing schedules for each form of vehicles in accordance with the resources required.

Gonza Alez et al. **[33**] applied both fuzzy logic and genetic algorithm for resource distribution. The model found the cost-minimized transportation schedule without deviating from supply constraints. It used fuzzy sets to represent initial information related to cost, demand and other variables. The scheduling task was solved by applying genetic algorithm with fuzzy fitness value for solution evaluation. To improve the flexibility in schedule planning and high success rate, D'Uffizi et al. [**29**] applied discrete event simulation that support in decision making during the planning for different activities. In the model, travelling time over the defined routes was supplied for each vehicle. Relief scheduling was designed on first-in-first-out basis where both preemption and non-preemption scenarios were considered for distribution policy. Lin et.al [**40**] used genetic algorithm with an immigrant scheme for staff scheduling. The model applied balancing between the preferred work shifts and intervals among the staff to generate efficient scheduling solutions.

It is hard to predict the time unit precisely and also transport network can dynamically change during the time varying scenarios. Considering the uncertainty, Sheuet al. [**17**] proposed fuzzy processing times and weights based on expert opinion of the tasks in emergency scheduling modelling with multiple objectives. In some scenarios such as in disasters, the corresponding shortest paths in the transportation network could vary with time if there are damaged points on the centres connecting network. Any path through that point is blocked thus cannot be used for computing the shortest paths. Multiple permutations and ranking measures based on disaster geography were applied for effective scheduling. For effective decision making during scheduling implementation, Baky **[32**] used Fuzzy Goal Programming (FPG) to minimize the degree of dissatisfaction of decision makers. It applied single decision makers at top level and multiple decision makers at lower level where the algorithm was extended to solve bi-level multi objective programming. Iteratively the re-evaluation was performed to increase the satisfaction level in decision making. The model applied membership functions to the objective functions and to the decision vectors in the upper level. The FPG was used to achieve the maximum degree of membership goals by minimizing their deviational variables and hence obtained the most satisfactory solution for decision makers. Coordination and cooperation between upper and lower level decision making is required for effective implementation. Topaloglu, S. and H. Selim [**51**] proposed a fuzzy goal programming model where multi-objective integer programming model was applied in a view of changeable factors that affect scheduling timetable and preferences considering the staff scheduling. The model was also able to cope with the uncertainties associated with target value of the management and staff preferences.

To minimize the unsatisfied demand at the receiving end, Yi et al. [**30**] proposed a meta-heuristic of ant colony optimization for the distribution scheduling. The scheduling model consisted of two phase decision making. The First phase dealt with vehicle route finding whereas the second phase dealt with the scheduling of vehicles and resources. Todorovic and Petrovic [**61**] proposed a staff scheduling with preference using a bee colony optimization which is able to eliminate some ineffective plan from the neighbourhood solution. The model performed scheduling in two phases. In first phase constructive search is applied where unscheduled shifts are assigned to available staff. In the second phase, the model applied local search to optimize the model and hence improve in the quality of scheduling.

Maenhout and Vanhoucke [**48**] created a population based Evolutionary algorithm to support planning for nurse allocation to the different departments in hospital under conditions of staff appointment, nursing shift in particular ward policies and personality traits. They applied immune cells to calculate objective function value for different objective functions. The objective functions with acceptable total objective function are selected. Bai et al. [**42**] proposed a hybrid evolutionary algorithm with the local search associated with simulated annealing hyper-heuristic with the better result. The model improved ability to handle constraints during scheduling. The algorithm showed enhancement in the performance level of evolutionary method by hybridizing with simulated annealing. Ray et al. [**58**] illustrated evolutionary algorithm for multi objective optimization where as Ngatchou et al. [**59**] applied pareto multi objective optimization.

Constantino et al. [**43**] proposed a new multiple assignment problems based deterministic heuristic algorithm to solve a nurse scheduling problem consisting of two phases. In first phase, constructive phase, complete schedule was developed by implementing successive assignment of task each day in the planning. In the second phase, improving phase, task assignments were resolved for better scheduling result. Hadwan et al. [**47]** proposed a Harmony Search Algorithm, population-based meta-heuristic algorithm, for the nurse scheduling problem for a hospital in Malaysia. The algorithm improved solutions iteratively based on good candidate solutions from the initial population by applying a stochastic random search on the solution with a number of alterations. Algorithm evolved upon the harmony memory and solutions were updated during the evolution. The test result showed better performance than the basic genetic algorithm. Wright and Vanhoucke [**53**] utilized heuristic procedure and exact solution for scheduling. Depending on the duration the method was selected. They chose exact solution approach if the planning length is less than 7 days and for higher than 7 days they applied meta-heuristic. The model utilised a multi-start heuristic to select combination of nurses randomly by adopting individual schedules. After then a random permutation was generated for those selected nurses. Moreover, an evolutionary algorithm and a branch-and-price approach were combined to reschedule planning to solve violated constraints for nurses from external department.

Gao and Lin [**46**] developed a mathematical model to overcome the scheduling problem that also covered different aspects and targets such as minimized cost and maximized efficiency. The goal of research was to find the maximum happiness level while nurses are working considering hospital regulation and then they used classical Particle Swarm Optimization to solve the problem to decrease the time-consuming manual scheduling. Akjiratikarl et al. [**38**] applied particle swarm optimization to schedule home care workers. They applied heuristic assignment scheme for scheduling. The heuristic assignment was mainly considered for transforming the continuous particle swarm optimization algorithm into the discrete job schedule.

4. Analysis and Discussion

We analysed several recent papers in the area of scheduling mainly focused on logistic distribution and staff scheduling. Distribution centre location and transportation and routing issues have impact on scheduling. Major objective and methodologies applied for the scheduling plans are surveyed. Tables 1, 2 3 and 4 shows the major objectives and methodology applied categorically in the area of positioning the service centres, transport and routing, logistic distribution and staff management scheduling. Most of the scheduling scenarios come with multi-objective like minimization in time, cost delay in service and maximization in performance level. Optimization is required to enhance the effectiveness of scheduling. To plan better scheduling, intelligent methods have been applied apart from the mathematical approach. Intelligent approach is highly suitable for non-linear and multi-objective optimizations task. In some cases hybrid approaches have also been applied.

Table 1: Methodologies and objective used with focused on pre-positioning, warehousing and clustering

Author	**Major Objective(s)**	**Methodology**
Zhi-Hua Hu and Zhao-Han Sheng (2015)	Rescue time optimization	Multi-Agent System.
Carmen G. Rawls and Mark A. Turnquist (2010)	Minimize the expected costs over all scenarios	Two-stage stochastic mixed integer program
Ann Melissa Campbell and Philip C. Jones (2011)	Minimize the sum of costs of serving each demand point from its closest supply point	Heuristic approach
F. Barzinpour and V. Esmaeili (2014)	Minimize cost	Multi-objective mixed-integer linear programming
Jiang-Hua Zhang et al. (2012)	Minimize cost of dispatching time	Integer mathematical programming ad Heuristic algorithm
HuseyinOnur Mete and Zelda B. Zabinsky	Minimize operating cost of warehouse, transport duration and unmet penalty	Two-stage stochastic programming model
Hossein Aghamomammadi	Minimize the time of relief operation and the number of fatalities	Heuristic method based on two nested Genetic Algorithms

Table 2: Methodologies and objective used with focused on transportation and connecting network

Author	Major Objective	Methodology
LinetÖzdamar and OnurDemir (2012)	Minimize the estimated total travel time and promotes efficient vehicle utilization	Mathematical Optimization
Yuan Yuan and Dingwei Wang (2009	Minimize total travel time along a path	Ant Colony Optimization
Yu-Jun Zheng and Hai-Feng Ling (2013)	Minimize the total time delay	Multi objective Fuzzy Optimization
Zhi-Hua Hu (2011)	Minimize cost	Integer linear programming

Chang WookAhn and R. S. Ramakrishna (2002)	Minimize cost associated with path	Genetic Algorithm
Thibaut Vidal et al. (2013)	Minimize cost and time	Hybrid Genetic Algorithm with adaptive diversity
Yuichi Nagata et al. (2010)	Minimize cost and time	Penalty-based edge assembly Memetic Algorithm
K. Zidi et al. (2013)	Maximize the number of saved people and minimize the costs of the rescue operation	Multi-Agents approach using a guided Genetic Algorithm
Enrique LoÂpezGonzaÂlez and Miguel A. RodrõÂguezFernaÂndez (2000)	Find the cheapest transporting schedule	Fuzzy System and Genetic Algorithm
LinetÖzdamar and Wei Yi (2008)	Minimize total service delay	Greedy Neighbourhood Search
Kergosien Y. et al. (2009)	Minimize travel distance	Integer linear programming

Table 3: Methodologies and objective used with focused on relief resource scheduling

Author	Major Objective	Methodology
Jiuh-BiingSheu et al. (2005)	Minimize distance cost and travel time between source and destination	Hybrid fuzzy-optimization.
Yu-Jun Zheng et al. (2015)	Minimize the total weighted waiting time of the tasks.	Biogeography-based optimization and fuzzy system
Jui-Sheng Chou (2014)	Minimize delay	Biological based Genetic Algorithm
Jos_e-Fernando Camacho-Vallejo et al. (2015)	Minimize the shipping costs and time	Bi-level mathematical programming
Gwo-HshiungTzeng et al. (2007)	Minimizing the total cost, travel time and maximize the minimal satisfaction during the planning period.	Multi-objective programming
Jiuh-BiingSheu (2007)	Maximize the time-varying relief demand fill rate and minimize the time-varying distribution costs	Hybrid fuzzy clustering-optimization
Jiuh-BiingSheu (2010)	Improve the performance of relief-demand management	Multi-source data fusion, fuzzy clustering, multi-criteria decision making
Yen-Hung Lin et al. (2011)	Minimize total unsatisfied demand, total travel time	Heuristic approaches of Genetic Algorithm and integer programming
Antonio D'Uffiziwt al. (2015)	Improve flexibility and relief success rates	Discrete event simulation
Wei Yi and Arun Kumar (2007)	Minimize the weighted sum of unsatisfied demand	Meta-heuristic of Ant Colony Optimization
Chang Chunguang et al. (2010)	Minimize task completion time and vehicle count.	Genetic Algorithm
Ibrahim A.Baky (2009)	Minimize the group regret of degree of satisfactions of all the DMs	Fuzzy Goal Programming and multi-objective linear programming

Fu-Sheng Chang et al. (2014)	Minimize unsatisfied demand for resources, time to delivery, and transportation costs	Greedy-search-based multi-objective Genetic Algorithm

Table 4: Methodologies and objective used with focused on staff management

Author	Major Objective	Methodology
ChananesAkjiratikarl et al. (2007)	Optimum home care workers scheduling	Particle Swarm Optimization and Heuristic Assignment scheme
Mankowska and DorotaSlawa (2014)	Optimum daily planning of health care services	Mathematical Modelling
Chun-Cheng Lin et al. (2015)	Balanced preferred work shifts and day-off of nursing staff	Genetic Algorithm with an immigrant scheme
Chun-Cheng Lin et al. (2015)	Maximize the total satisfaction of the nursing staff with their preference rights and interests	Memetic Algorithm with Recovery Scheme
Bai, R. et al. (2010)	Improve the constraint handling ability,	Penalty based Genetic Algorithm and Simulated Annealing hyper-heuristics
Constantino, A. A. et al. (2013)	Maximize the satisfaction of nurses’ preferences and minimize the violation of soft constraints.	Multi assignment Heuristic Algorithm
Fan, N. et al. (2013)	Balance the preferences of the employees	Integer Programming
Felici, G. and C. Gentile (2004)	Maximise staff satisfaction	Integer programming
Gao, S. C. and C. W. Lin	Minimise cost and balance nurses' happiness	Particle Swarm Optimization (PSO)
Hadwan, M. yet al. (2013)	Allocate the required workload to the available staff	Harmony Search Algorithm
Maenhout, B. and M. Vanhoucke (2013)	Cope with schedule disruptions for the staff shift	Artificial Immune System
M’Hallah, R. and A. Alkhabbaz (2013)	Cope with real time context dependent constraints	Mixed integer program
Topaloglu, S. and H. Selim (2010)	Treat uncertainties in the target value of the hospital management and nurses preference	Fuzzy Goal Programming
Wright, P. D. and S. Mahar (2013)	Minimize costs and reduced overtime result for multiple units	Heuristic Algorithm
Wright, P. D. and M. Vanhoucke (2013)	Understanding in the consequences and outcomes of various personnel re-rostering characteristics and strategies.	Artificial Immune System Heuristic Procedure
Cai,X., &Li,K.N (2000)	Minimize the total cost for assigning manpower	Genetic Algorithm with multi-criteria Optimization
Nikola Todorovic and SanjaPetrovic (2013)	Handle with the nurse rostering problem by minimizing the use of outside nurses	Bee Colony Optimization Algorithm

5. Conclusion and future directions

Distribution of resources and allocation of staff requires a careful planning. Scheduling provides the enhanced and efficient way of planning. Each scheduling scenario has its own objectives and constraints in terms of cost, delay time, resource limitation. Meeting all constraints at a time is complex therefore optimization is required for effective scheduling. Different techniques, models and algorithms are applied for scheduling optimization including mathematical and computational approaches. For multi-objective scheduling scenarios computational intelligent approaches have been used effectively in diverse ways which includes fuzzy logic, genetic algorithm, heuristic methods, swam optimization, ant colony optimization, agent system. This survey paper covers approaches applied by many authors in recent times for scheduling in the area of relief distribution and staff scheduling. Finding appropriate locations or aligning them into appropriate groups has been applied in different ways to enhance the effectiveness of the scheduling plan. It is analysed through many papers that finding appropriate path and vehicles for resource transfer also play role in scheduling effectiveness. For this, wide ranges of approaches were applied. Cautious planning of distribution of resources, careful setting up of staff allocation can be done using different methods. Hybrids methods can be applied to optimize the scheduling performance. The paper provides the methods and techniques that are applied in the area of relief and staff scheduling along with the limitations.

Surveying many papers exposed some the issues for further research in the area of resource and staff scheduling. Improvement in the performance of demand management is required for the effective, timely and fair distribution. The nature of demand is stochastic and also there is uncertainty of requirements in most of the scenarios so forecasting mechanism needs to more dynamic and exact. An appropriate grouping and priority identification of the demand is needed for the optimum scheduling result. Also, inclusion of the transportation path, vehicles availability, capacity and preferences are desirable in scheduling. Alteration in methods and algorithm is required for multi-objective scheduling plan.

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